Uber Happy? Work and Well-being in the "Gig Economy"[1]

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Summary

We study the rise of the so-called "gig economy" through the lens of Uber and its drivers in the United Kingdom. Using administrative data from Uber and a new representative survey of London drivers, we explore their backgrounds, earnings, and subjective well-being. We find that the vast majority of Uber drivers are male immigrants, primarily drawn from the bottom half of the London income distribution. Most transitioned out of permanent part- or full-time jobs and about half of drivers' report that their incomes increased after partnering with Uber. After covering vehicle operation costs and Uber's service fee, we estimate that the median London driver earns about £11 per hour spent logged into the app. But while Uber drivers remain at the lower end of the London income distribution, they report higher levels of life satisfaction than other workers. Consistent with a trade-off between evaluative and emotional well-being observed among the self-employed, they also report higher anxiety levels. We hypothesize that the higher life satisfaction among Uber drivers partly reflects their preferences for flexibility and the autonomy that the platform offers. We provide suggestive evidence showing that drivers who emphasize flexibility as an important motivation to join Uber also report higher levels of subjective well-being. However, a minority of drivers who report that they would prefer work as an employee report lower levels of life satisfaction and higher levels of anxiety. Overall, our findings highlight the importance of non-monetary factors in shaping the welfare of workers in the gig economy.

JEL: O18, J31, J81, D60
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1. Introduction

Life satisfaction and several other facets of subjective well-being (SWB) are deeply intertwined with an individual's income, employment, and working conditions.[2] Despite this fact, little is known about how workers fare in alternative work arrangements, which are becoming a prominent feature of 21st-century labour markets.

In the United Kingdom, the pronounced increase in self-employment, around the turn of the century, has more recently been accompanied by the rise of so-called 'gig work'.[3] In particular, the spread of Uber—often hailed as the flagship of the gig economy—has given rise to a spirited debate.[4] On the one hand, it has been argued that Uber extends the opportunity to become a 'micro-entrepreneur' to groups often marginalized in the traditional labour market. By giving individuals full autonomy over working time, it allows drivers to achieve work-life balance and provides opportunities to earn additional income when needed. On the other, in a report entitled *Sweated Labour: Uber and the Gig Economy*, one influential Labour MP suggests that pay and working conditions for the country's Uber drivers are grim—the term 'sweated labour' was coined in Victorian Britain to describe work involving drudgery, long hours, and low wages. While these narratives provide two diametrically opposed views of gig work, they have one thing in common—they both rely on anecdotal accounts. Unfortunately, we have limited systematic evidence on who actually works in the gig economy and how they fare relative to those in traditional work arrangements more broadly.

In this paper, we explore work and well-being of workers in the gig economy through the lens of Uber and its 'driver-partners'.[5] Using anonymized administrative data from Uber, official government surveys, and a new independent survey carried out by the polling company ORB of a representative sample of 1,001 active UberX and UberPOOL drivers in London in March 2018, we explore several fundamental questions to help inform the discussion.[6] Who becomes an Uber driver? Are drivers primarily drawn from economically disadvantaged backgrounds? Are they previously unemployed workers who have turned to Uber as a last resort? And how do they fare in terms of income and well-being relative to the rest of the working population?

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[2] See, for example, Freeman (1978), Blanchflower and Oswald (1998), Blanchflower (2000), Blanchflower et al. (2001), Benz and Frey (2008), Frey and Stutzer (2010), De Neve and Ward (2017), and Lindqvist et al. (2018).

[3] Self-employment in the U.K. has seen significant growth in recent years, rising from 12 percent of the labour force in 2001 to over 15 percent in 2017, which partly reflects the expansion of alternative work arrangements such as gig work. Indeed, recent estimates by Balaram et al. (2017) suggest that if the British gig economy was an organization, it would be about as large as the National Health Service (NHS).

[4] Although we focus on the debate concerning the labor market of Uber drivers, a related debate and literature concerns how the rise of digital ridesharing firms such as Lyft and Uber affects incumbent taxi drivers (Berger et al., 2018), public transit (Hall et al., 2018), or congestion and motor vehicle fatalities (Barrios et al., 2018).

[5] For brevity referred to as 'Uber drivers' or simply 'drivers' throughout the paper.

[6] Among the services provided through Uber, its low-cost alternatives UberX and UberPOOL, which provide point-to-point transportation using a standard private hire vehicle, are by far the most popular among drivers. Consequently, we focus on drivers using the UberX and UberPOOL services since they are the most representative of the London driver pool.

We begin our analysis by exploring who Uber drivers are, comparing the demographic composition of the driver pool with other London workers. We document that drivers overwhelmingly are male immigrants often drawn from Black, Bangladeshi, and Pakistani ethnic groups. Yet, we find little evidence to suggest that the typical London driver has turned to the gig economy due to the absence of work in the conventional labour market. A negligible share of drivers transitioned out of unemployment. Instead, the vast majority held permanent part- or full-time jobs, mostly in distribution, transportation, or services prior to joining Uber. Moreover, while driving with Uber is the main source of work for most drivers, about a quarter continue to hold other jobs, or own a business.

Turning to drivers' earnings, we find that Uber drivers are drawn from the bottom half of the London income distribution: the median self-reported gross weekly income (i.e., including income streams other than Uber) among drivers is £460, which is considerably lower than the £596 median gross weekly pay among London workers in the January—March 2018 Labour Force Survey (LFS). Almost three-quarters of Uber drivers earn less on a weekly basis than the median London worker. Yet, about half state that their income increased after becoming an Uber driver, which presumably reflects that many drivers transitioned out of low-paying blue collar or service jobs. But while these findings show that Uber drivers are drawn from the lower end of the London income distribution, they remain silent about the income that drivers derive from driving with Uber.

A complicating matter in estimating drivers' earnings from Uber is that they, like most other self-employed black cab and private hire vehicle (PHV) drivers, have to cover the costs of operating their vehicles. These costs, such as commercial insurance and petrol, are only observed by the individual driver. Thus, while it is straightforward to show that the median London driver received an average hourly payout of £16.50 from Uber (net of its 'service fee') in January—March 2018, based on data registered in the Uber app, this does not capture their earnings after covering their costs. To estimate expenses incurred while driving with Uber, ORB therefore surveyed drivers on their expenditure on car rental or financing repayments, insurance, and petrol. We complement these data with independent estimates of the cost of car tax, depreciation, and maintenance for the vehicle fleet operated by the drivers in our sample, as well as estimates by Transport for London (TfL) on the costs of becoming a licensed PHV driver, which is a requirement to drive with Uber in the United Kingdom. Using these different sources of data, we construct estimates of the expenses incurred while driving with Uber.

Our estimates suggest that the median Uber driver in London earns about £11 per hour spent logged into the app, after deducting Uber's service fee and drivers' expenses. We note that these estimates should be interpreted cautiously, given the challenges involved in estimating the costs that drivers have to bear and the difficulties associated with accurately measuring working time in flexible work arrangements.[7] Yet, reassuringly, we obtain similar estimates when we instead rely on drivers' self-reported income and hours worked. While these estimates suggest that being an Uber driver is low-paid work, it seemingly provides similar earnings to lower-paying jobs held by many immigrants in the conventional London labour market.[8]

However, a growing body of work shows how a wide range of job characteristics beyond monetary compensation affect individuals' SWB (e.g., Frey and Stutzer, 2010; De Neve and Ward, 2017). The fact that many Uber drivers may have selected into a flexible work arrangement to gain greater autonomy over their working hours suggests that such dimensions might affect their well-being. Indeed, the majority of surveyed drivers point to autonomy, scheduling flexibility, or improved work-life balance as reasons for joining the Uber platform. Most also state that they would require significant earnings increases to accept working a fixed schedule, which suggests a high willingness to pay for such flexibility. Consistent with these survey responses, administrative data shows that drivers use their discretion over hours to significantly adjust their working time: over a third of drivers adjust the hours they spend logged into the Uber app by at least 50 percent on a week-to-week basis. Consequently, comparing how Uber drivers fare in relation to workers in traditional jobs in purely monetary terms potentially leaves out important job amenities that studies have shown to be highly valued by drivers (e.g., Angrist et al., 2017; Chen et al., 2017; Hall and Krueger, 2018).

Against that backdrop, we analyze how the SWB of Uber drivers compare with other London workers. In our analysis, we follow a vast literature in economics and psychology and explore two distinct domains of SWB: life evaluation measures, which are based on individual assessments of well-being over a longer time horizon, and emotional well-being, which measures the quality of an individual's everyday experience through the lens of emotions such as anxiety or happiness (see Kahneman and Krueger, 2006, and Kahneman and Deaton, 2010). To measure SWB, we use identical survey instruments as the Office of National Statistics (ONS), which allows us to pitch Uber drivers against other London workers in terms of life evaluation (life satisfaction and worthwhileness) and emotional well-being (happiness and anxiety).

We find that Uber drivers report higher average levels of life satisfaction and worthwhileness in the March 2018 ORB survey compared to employed and self-employed London workers in the April 2017—March 2018 Annual Population Survey (APS). The flipside of this is that they also report higher levels of anxiety. An apparent trade-off between life satisfaction and anxiety speaks to a growing body of work

[7] See Harris and Krueger (2015) for a discussion of the 'immeasurability of hours' in flexible work arrangements, which may arise in our context if drivers, for example, are engaging in 'multiapping' (i.e., spend time logged into several ridesharing apps simultaneously). However, a very small share of drivers in the ORB survey (less than three percent) report that they use other ridesharing apps in addition to Uber suggesting this is unlikely to affect our estimates. We return to this discussion below.

[8] While the minimum wage legislation does not apply to self-employed workers, it is also interesting to note that median driver earnings are higher than the National Living Wage for employees aged 25 and over (£7.50 during the period under consideration), as set by the UK government, as well as the London Living Wage (£10.20 in 2017-18), which is voluntary and set by the Living Wage Foundation. We note, however, that direct comparisons are complicated by the existence of additional benefits (e.g., holiday pay) that may not be included in conventional pay rates.

demonstrating that while self-employed workers typically state that they are more satisfied with their lives (e.g. Blanchflower and Oswald, 1998; Blanchflower, 2000; Blanchflower, et al., 2001), they also experience higher levels of negative emotional well-being like anxiety and stress (e.g., De Neve and Ward, 2017).

At first glance, the higher life satisfaction and relatively low hourly earnings of Uber drivers is at odds with a large literature documenting that evaluative well-being measures are typically positively correlated with an individual's level of income (e.g., Stevenson and Wolfers, 2008; Kahneman and Deaton, 2010; Frijters, Haisken-DeNew, and Shields, 2002). Yet we find at best a weak link between a variety of alternative income measures and SWB among drivers. However, drivers' perceptions of how their incomes *changed* after partnering with Uber is a key predictor of differences in life satisfaction. Intuitively, drivers that transitioned to Uber from lower-paid work are more satisfied with their lives, consistent with earlier work documenting how *relative* income matters in shaping individuals' aspirations and SWB (e.g., Clark and Oswald, 1996; Ferrer-i-Carbonell, 2005; Luttmer, 2005; Clark, Frijters, and Shields, 2008).

A possible explanation for the observed gap in SWB is that it arises due to compositional differences between Uber drivers and the broader London workforce. However, a decomposition exercise that adjusts for factors such as age, educational attainment, ethnicity, and income, suggests that the higher SWB among London's Uber drivers relative to workers in traditional forms of employment is not driven by observable group-level differences. We instead hypothesize that part of this unexplained gap relates to the apparent preferences for flexible work among the majority of drivers. Indeed, we find no link between working time and SWB, which plausibly reflects the fact that drivers can match actual working hours to their working time preferences. We also provide suggestive correlations showing that drivers who state that they partnered with Uber to take advantage of the flexibility the platform offers also exhibit substantially higher SWB. Conversely, the minority of drivers that would prefer to be classified as an employee rather than independent contractor exhibit levels of life satisfaction similar to other London workers in road transportation, as well as higher levels of anxiety.

While these correlations should not be interpreted as causal links, they are suggestive of flexibility playing a role in shaping well-being among individuals in independent work arrangements. Most individuals selecting into such arrangements, at least on the Uber platform, seemingly have strong preferences for autonomy and scheduling flexibility. Indeed, recent evidence from the United States suggests that the real-time flexibility enables Uber drivers to earn about twice the surplus they would in a less flexible work arrangement (Chen et al., 2017). Drivers also use their choice over hours to significantly adjust their working time at daily or weekly intervals (Hall and Krueger, 2018), and many have preferences for driving under a flexible ridesharing arrangement, rather than a fixed-fee system (Angrist et al., 2017). We add to this literature by documenting that Uber drivers in London also exhibit higher levels of SWB than other workers in traditional employment. While we cannot directly identify underlying mechanisms, we provide suggestive evidence that at least part of the higher SWB among

London Uber drivers stem from a matching between (most) drivers' preferences for flexible work and the autonomy that the platform offers. In our view, this provides one plausible explanation for the fact that a growing share of workers are trading the benefits associated with a traditional nine-to-five job for work in the gig economy, even if the latter oftentimes provides less protection, stability, and lower monetary rewards (e.g., Abraham et al., 2017; Katz and Krueger, 2016; Harris and Krueger, 2015; Hara et al., 2017).[9]

Figure 2.1: Uber's expansion in UK cities, 2013-2018.

---FIGURE 2.1 HERE---

Notes: Monthly number of active drivers in Birmingham, Leeds, London, and Manchester based on internal aggregated administrative data from Uber. Active drivers are defined as those providing at least four trips in each respective month.

2. Who becomes an Uber driver?

Since its UK launch in 2013, Uber's driver pool has grown exponentially. However, identifying the number of Uber drivers is complicated by the fact that drivers have full discretion over their working hours: the labour supplied by drivers may thus vary significantly at daily, weekly, or monthly frequencies. To circumvent this issue, Hall and Krueger (2018) define an 'active' Uber driver as someone who completes at least four trips in a given month. According to this definition, there were almost 50,000 active London drivers registered with Uber in March 2018. As shown in Figure 2.1, the bulk of Uber drivers in the UK work in London, which motivates our focus on the capital city. In the subsequent analysis, we rely on a representative sample of 1,001 drivers from the London driver pool surveyed by ORB to elicit information on driver characteristics and their motivations for becoming an Uber driver.[10]

Table 2.1: A snapshot of the London labour force, 2018.

	Uber drivers (1)	All workers (2)	Self-employed (3)	Taxi, cab drivers, and chauffeurs (4)
Aged 18-29	12%	23%	13%	0%
Aged 30-39	40%	30%	25%	26%
Aged 40-49	32%	23%	26%	33%
Aged 50-64	16%	22%	29%	35%
Aged >65	0%	3%	8%	6%
Female	1%	44%	34%	3%
Married	70%	51%	57%	81%
Children in household	64%	42%	42%	63%

[9] In a broad sense, this is also consistent with the fact that self-employment in general often does not pay more, suggesting that the self-employed are willing to forego income for a higher degree of autonomy and independence at work (Hamilton, 2000).

[10] We use additional criteria (e.g., that drivers have worked at least eight distinct weeks in the last year) to define the pool of London drivers from which we draw the sample of 1,001 drivers. These criteria and the survey are described in more detail in the Appendix and at: https://www.orb-international.com/2018/10/02/uberhappy/. Additionally, in the Appendix we also document that the sample of 1,001 drivers is representative of the London driver pool that fulfil the sample selection criteria (approximately 38,000 drivers in total) in observable dimensions such as hours worked, payouts, and tenure on the platform.

Less than high school	13%	24%	28%	66%
High school degree	24%	15%	13%	18%
Some college	31%	7%	7%	4%
College degree	32%	54%	51%	12%
In education or training	9%	18%	12%	3%
Immigrant	82%	40%	47%	72%
Asian (any other)	10%	3%	2%	5%
Bangladeshi	14%	2%	2%	14%
Black	23%	9%	7%	18%
Chinese	0%	1%	1%	0%
Indian	5%	7%	6%	3%
Mixed/multiple	1%	2%	2%	2%
Other ethnic group	11%	4%	5%	6%
Pakistani	15%	2%	2%	17%
White British	6%	51%	48%	21%
Other White	16%	18%	24%	13%
Observations	1,001	5,603	985	56

Notes: Data for Uber drivers is drawn from the ORB survey of London drivers. Data for other London workers is based on the January—March 2018 LFS restricted to employed and self-employed respondents aged 18 and above that report Central, Inner, or Outer London as their region of place of work. We exclude respondents in the ORB and LFS survey with missing responses on a question-by-question basis and weight all responses from the LFS using the supplied person weights. 'Children in household' is based on children below the age of 18 in the ORB survey and below the age of 19 in the LFS. 'In education or training' corresponds to drivers stating that they are 'Studying to obtain more qualifications' in the ORB survey and respondents that report being 'in education/training′ in the LFS. Immigrant status is based on the question 'Did you immigrate to the United Kingdom?' in the ORB survey, and country of birth as recorded in the LFS. As described in the main text, the ORB survey used more widely used educational classifications (e.g., 'college') to reflect the fact that most drivers are unlikely to have UK qualifications. We aggregate responses in the ORB survey to less than high school (no schooling complemented, nursery school, some high school), high school degree (high school graduate), some college (some college credit, no degree; trade/technical/vocational training), and college degree (associate, bachelor's, master's, professional, and doctorate degree). In the LFS data, we classify 'GCSE grades A*-C or equivalent', 'Other qualification', and 'No qualification' as 'less than high school'; 'GCE A level or equivalent' as 'high school degree'; while 'Higher education' and 'Degree or equivalent' is classified as 'some college' and 'college degree' respectively. 'Black' corresponds to 'African/Caribbean/Black British' and 'Other White' also includes those identifying as 'White Irish'.

2.1. Driver demographics

Table 2.1 presents the demographic composition among the sample of 1,001 Uber drivers based on the ORB survey and three comparison groups: all London workers, the self-employed, and well as taxi and cab drivers (i.e., also including Uber drivers) based on the January—March 2018 LFS.

A majority of Uber's drivers are in their 30s or 40s and thus overwhelmingly prime-aged relative to the general London workforce.[11] Conversely, a comparison with the broader taxi population suggests that those who drive with Uber tend to be somewhat younger than the typical black cab or PHV driver. Since drivers are older than other London workers on average, it is unsurprising that marriage rates are higher among both Uber drivers and the broader taxi workforce. Both groups are also more likely to have

[11] We impute the age of drivers that provided a binned age response (aged 18-24, 25-34, etc.) in the ORB survey using the mean age of respondents with numeric responses within each age bin.

children in their household. Notably, similar to the general black cab and PHV driver workforce, the Uber driver pool has an extreme underrepresentation of women.

In contrast, immigrants are vastly overrepresented among Uber drivers. Among those reporting immigrant status some 82 percent state they immigrated to the UK, which is more than twice the share observed among the general London workforce. Immigrants are also overrepresented in the broader black cab and PHV driver population, though the share among Uber drivers is slightly higher. Notably, few immigrant Uber drivers are recent arrivals: the mean year of immigration is 2001, and almost 90 percent of immigrant drivers have resided in the UK for more than five years. A large share of immigrants among Uber drivers is also mirrored in an overrepresentation of several ethnic minority groups. In particular, Black, Bangladeshi, and Pakistani groups are all vastly overrepresented compared to the London workforce. Conversely, individuals that identify as White British constitute a much smaller share of Uber drivers than in the labour force, or indeed the full population of London black cab and PHV drivers.[12]

Uber drivers overwhelmingly come from immigrant backgrounds, yet exhibit high levels of educational attainment. Among those reporting educational attainment, more than half (63 percent) report having at least some college credits or a degree including technical, trade, and vocational training; respectively 18 and 6 percent have received a Bachelor's or Master's degree. When reclassifying UK educational qualifications of the London workforce in the LFS to map onto the categories used in the ORB survey, we find that Uber drivers tend to have an educational composition that broadly mirrors the London workforce.[13] In other words, they have substantially higher educational attainment on average when pitched against the broader taxi and PHV driver population. Individuals that drive with Uber thus tend to be more educated than the average London driver.

Overall, the Uber driver pool closely resembles the composition of the broader black cab and PHV driver workforce, with the main exception of their relatively higher educational attainment. Yet, while the demographic characteristics in table 2.1 shed new light on the backgrounds of Uber drivers in London, they say little about the factors shaping drivers' decision to join the platform. We next examine the employment history of London drivers and discuss the role of income and flexibility in shaping the decision to start driving with Uber.

Table 2.2: What were drivers doing before Uber?

A. What were drivers doing prior to becoming an Uber driver?

Working full time	64%	A caregiver	1%
Working part time	23%	A student	5%

[12] Note that this conceals significant differences in ethnic composition between black cab and PHV drivers that are clearly evident when breaking down ethnicity by driver status: http://content.tfl.gov.uk/taxi-and-phv-demographic-stats.pdf.

[13] In light of most drivers having immigrant backgrounds, the ORB survey used more widely used classifications of educational attainment (high school, college, etc.) to encompass the fact that drivers are likely to have qualifications from different (non-UK) education systems. See the notes to Table 2.1 for further details on the mapping of educational qualifications.

Working multiple jobs	4%	Retired/pensioned	0.3%
Unemployed	2%	Other	4%

B. Which sectors were Uber drivers previously employed in?

Agriculture, forestry and fishing	1%	Manufacturing	3%
Banking and finance	3%	Other services	23%
Construction	6%	Public admin, education and health	8%
Distribution, hotels and restaurants	12%	Transport and communication	43%
Energy and water	1%		

C. What type of occupation did Uber drivers previously hold?

White-collar (professional or managerial)	19%	Service job (e.g., cashier, waiter)	37%
White-collar (administrative or clerical)	6%	Other	10%
Blue-collar	27%		

Notes: Panel A tabulates responses to the question 'Prior to driving with Uber were you …?' based on the ORB survey of 1,001 Uber drivers in London. Note that a respondent could give multiple answers. Panels B and C tabulates responses to the questions 'And in which industry were you employed?' and 'And would you describe that job as ...' among drivers that were working prior to becoming an Uber driver.

2.2. Motives for joining the Uber platform

Table 2.2., panel A, tabulates responses from the ORB survey concerning the employment history of drivers. A majority of respondents were employed either full- or part-time (64 and 23 percent respectively) prior to partnering with Uber. Among those previously working, most (80 percent) described their previous job as 'a permanent job that would be there until they left it, got fired, or laid off'. Just two percent reported being unemployed prior to joining the platform, which suggests that most drivers did not partner with Uber due to a failure to find permanent work in the conventional labour market. Instead, most drivers who previously were working transitioned out of employment in the transport and communication sector (43 percent), while about one third were previously working in the services sector, including distribution, hotels, and restaurants (see panel B).

A potential motive for partnering with Uber is the possibility of earning additional income. To shed light on where in the London income distribution Uber drivers are drawn from, we examine their self-reported *total* weekly income.[14] Figure 2.2 compares the distribution of gross weekly pay among workers in London based on data from the January—March 2018 LFS and self-reported income of Uber drivers in the ORB survey. Uber drivers are typically drawn from the bottom half of the income distribution: nearly three-quarters (72 percent) of individuals driving with Uber have a lower gross weekly income than the *median* London worker's pay, while about 90 percent of drivers report a

[14] The precise wording of the question in the ORB survey is: 'Thinking about your total average monthly income (before tax), what is your average monthly income?'. For drivers refusing to report numeric responses, we impute monthly income for respondents that instead provided a binned response using the mean income within each bin among respondents with non-missing numeric responses.

lower income than the *average* gross weekly pay.[15] Lower earnings among drivers presumably partly reflects the fact that Uber drivers tend to belong to groups (e.g., immigrants) that exhibit lower average incomes in the London labour market.

Figure 2.2: Gross weekly income/pay among Uber drivers and London workers, 2018.

---FIGURE 2.2 HERE---

Notes: Kernel density plots of self-reported weekly income among Uber drivers in London based on data from the ORB survey and gross weekly pay among respondents aged 18 and above that report Central, Inner, or Outer London as their region of place of work in the January—March 2018 LFS weighted by the supplied income weights. We present data both for all employed workers, as well as for workers employed in distribution, hotels, and restaurants; transport and communication; and other services, respectively. Weekly income for Uber drivers are calculated based on the self-reported average monthly total pre-tax income (i.e., also including income streams other than Uber) scaled to a weekly level.

At the same time, despite the relatively low income levels of drivers, most state that their incomes increased after they started driving with Uber. Almost half (45 percent) of respondents' in the ORB survey say that their income increased 'a little' or 'a lot', while less than one in five (19 percent) state that their incomes decreased. An increase in income after partnering with Uber and relatively low weekly earnings can potentially be reconciled by noting that most drivers transitioned out of blue collar and services jobs with presumably low levels of pay (see Table 2.2, panel C).

According to previous survey results of Uber drivers in the United States (Hall and Kruger, 2018), one of the main motivations for partnering with Uber is the perceived flexibility that the platform offers. Indeed, Uber drivers are not obliged to drive a specific number of hours, and they are able to go offline at any time. Moreover, drivers are able to take on trips through traditional minicab operators or other ridesharing apps, and are under no obligation to accept trips when online in the Uber app.[16]

Against that backdrop, flexibility indeed emerges as a seemingly important motivation to become an Uber driver also in London. The vast majority of surveyed drivers 'agree' or 'strongly agree' with the statements 'Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage' (82 percent) and 'I don't want to work for a traditional company in case I lose the flexibility I have' (84 percent). Similarly, almost all (93 percent) agree with the statement 'I partnered with Uber to have more flexibility in my schedule and balance my work life and family'. Moreover, 80 percent of drivers' say that they prefer flexible over fixed hours when directly asked. Within this group, the median driver further stated that he would require a 25 percent hourly pay increase to accept working fixed rather than flexible hours.[17]

[15] Note that while the ORB data contains information on Uber drivers' *income*, the LFS data only reports data on *pay*, which likely underestimates the income of other London workers to some extent.

[16] While drivers tend to emphasize the role of flexibility as an important motivation for partnering with Uber, others argue that Uber and other digital platforms leverage considerable control over independent workers. Rosenblat and Stark (2016), for example, suggest that Uber exerts 'soft control, affective labor, and gamified patterns of worker engagement on its drivers'. See Prassl (2018) for a recent overview of this argument.

[17] Drivers were first asked: 'Would you prefer to work fixed hours rather than the fully flexible hours you have now?'. The 80 percent of drivers that stated that they do *not* prefer fixed over flexible hours were

Thus, most drivers emphasize the role of autonomy and having choice over working hours as a motivation to join the Uber platform and have a seemingly high willingness-to-pay for such forms of flexibility. In light of this, it is unsurprising that the majority (81 percent) of respondents' state that they prefer to remain independent contractors rather than be classified as an employee and lose the flexibility of setting their own schedule.[18]

Another way to gauge the role of flexibility and work-life balance is to examine other (work) activities that individuals combine with driving with Uber. About a quarter of drivers report such work-related activities including holding other full- (10 percent of respondents) or part-time (12 percent) jobs, or having their own business (6 percent), in addition to driving with Uber. Thus, there are seemingly complementarities between independent work and more traditional employment (e.g., Koustas, 2018), at least for some. Some drivers also act as caregivers for a relative or friend (7 percent), or are studying to obtain more qualifications (9 percent), which further points to some of the ways independent work may be well suited to those with other commitments.

In sum, these findings suggest that the typical Uber driver in London is not a marginalized worker that has been squeezed out of the conventional labour market. Most drivers left permanent employment to start driving with Uber and were seemingly attracted to the platform by the flexibility it offers. Moreover, while most Uber drivers report low incomes relative to other London workers, about half also say that their incomes increased after partnering with Uber, which presumably reflects that many drivers transitioned out of low-paid blue collar and service jobs. Yet, while most drivers seem content with their work arrangements, we note that a minority of drivers would prefer fixed hours and traditional employment arrangements.

3. Uber drivers' pay and working hours

Our analysis in the previous section uncovered that Uber drivers tend to be drawn from economically disadvantaged groups with most drivers reporting lower incomes than the typical London worker. An important drawback of these income estimates, however, is that while they tell us how drivers fare economically, they are silent on drivers' income streams from Uber itself. Thus, in this section we turn to examining drivers' income from driving with Uber. In a first step, we use anonymized administrative data collected through the Uber app to shed light on the distribution of payouts and working time among drivers. We then proceed to estimate the expenses incurred while driving, which allows us to estimate the hourly earnings drivers receive after these costs and Uber's service fee have been deducted.

subsequently asked: 'Say you were given the opportunity to switch to set hours with Uber, rather than the fully flexible driving hours you have now. How much would your hourly income need to increase for you to accept those set, non-flexible working hours?'

[18] Drivers were asked whether they preferred to 'remain an independent contractor for Uber so I can keep the flexibility to choose when and where I drive and set my own schedule, but not be eligible for things like a guaranteed minimum wage (currently £7.50 per hour) and holiday pay' or 'be classified as a worker or employee of Uber so I could be eligible for things like a guaranteed minimum wage (currently £7.50 per hour) and holiday pay, even if that means having less flexibility to set my own schedule or being told when and where to drive and which trips to accept'.

3.1. A view of payouts and working hours from administrative data

Uber drivers are paid for each trip they drive according to a predetermined formula: in London, drivers on UberX receive a base fare of £2.50, plus £1.25 per mile and £0.15 per minute while on a trip with a minimum fare for any trip of £5. A system of dynamic pricing (‘surge pricing’) applies a multiplier to fares in areas of high demand, which induces significant spatial and temporal variation in fares. Payouts are made directly to drivers after Uber deducts its ‘service fee’, which stands at either 20 or 25 percent depending on when a driver joined the platform.[19]

We begin by examining the distribution of these payouts in the sample of 1,001 London drivers drawing on administrative data collected through the Uber app over the period 1st January—31st March, 2018. Throughout most of the subsequent analysis, we focus on mean hourly payouts that are calculated as total payouts net of Uber’s service fee divided by the total number of hours spent logged into the Uber app, which constitutes a common definition of hours worked on the platform (e.g., Chen et al., 2017).[20]

Figure 3.1: Mean hourly payouts for Uber drivers, 2018.

---FIGURE 3.1 HERE---

Notes: Mean hourly payouts net of Uber’s service fee between January—March 2018 for the sample of 1,001 Uber drivers in London based on anonymized internal administrative data from Uber. For presentational purposes, we exclude one driver with an exceptionally high mean hourly payout (£65) over the sample period.

Figure 3.1 graphs the distribution of mean hourly payouts for the London drivers in our sample, which is virtually identical to the distribution of payouts among the full population of drivers (see Figure A.1). The median driver receives an hourly payout of £16.50 net of Uber’s service fee.[21] To put this figure in perspective, a report commissioned by TfL in 2016 estimated average hourly revenues among licensed London black taxi drivers at £13.44 (Le Masurier et al., 2016, p.29). Yet, there is notable variation in mean hourly payouts among Uber drivers: the interquartile range spans £14.84 to £18.17. This variation in hourly payouts raises the question of potential productivity differences between part-time drivers, which spend only a few hours per week driving, and those who drive full time.

[19] In our data, total payouts is the sum of all trip-related payouts (including trip incentives such as surge pricing, tips, etc.), referral bonuses and any other promotions that a driver may have received. However, we note that referrals and promos constitute less than 0.25 percent of total payouts among London drivers.

[20] Although hours spent logged into the Uber app constitutes a straightforward measure of hours worked, it comes with a number of potential drawbacks. For example, drivers are not obligated to accept trips and are free to ignore incoming trip requests, which means that drivers in principle can be logged into the app while doing other work or being at home. At the same time, hours spent logged into the app does not include, for example, time spent cleaning the car etc. and may thus constitute a blunt measure of hours actually ‘worked’. Again, this highlights the ‘immeasurability of hours’ in flexible work arrangements (see Harris and Krueger, 2015).

[21] It is informative to note that the mean hourly payout of £16.49 across drivers is nearly identical to the mean payout received by the median driver in our sample. Also, note that the mean hourly payout in January—March in our sample is slightly lower than the mean hourly payout between June 2017—June 2018 across all active London drivers that fulfil the criteria outlined in the Appendix (see Figure A.2).

To elucidate the distribution of working time, Figure 3.2a displays the mean weekly hours spent logged into the Uber app and time spent 'on trip' (i.e., logged into the app spent en route to pick up a passenger, or with a passenger on board) respectively. The median driver spends on average 30 hours logged into the app and about 19 hours on trip per week. Thus, Uber constitutes an important source of work for many drivers. However, a comparison with weekly working hours among other London workers suggests that Uber drivers work fewer hours, when measured by time spent in the Uber app.[22] In the January—March 2018 LFS, for example, the median London employee and taxi driver reported working respectively 39 and 35 hours in the reference week, while other estimates suggest an average working week of 40 hours among London black cab drivers (Le Masurier et al., 2016, p.29).[23]

Another interesting takeaway from Figure 3.2b is that Uber drivers spend a large percentage of the time they are logged into the app on a trip. Among the drivers in our sample, on average about 65 percent of the time logged into the app is spent en route to pick up a passenger, or with a passenger on board. In contrast, estimates reported by TfL shows that average 'non-hired time' among licensed London black taxis is 54 percent (Le Masurier et al., 2016, p.28); taxis are thus only carrying a fare 46 percent of the time, though direct comparisons with Uber drivers is complicated by the fact that most conventional taxi trips are hailed on the street or from a rank. However, the seemingly higher capacity utilization among Uber drivers in London is consistent with more direct comparisons of Uber and taxi drivers in major US cities (Cramer and Krueger, 2016).

Figure 3.2: Weekly hours driving with Uber, 2018.

---FIGURE 3.2a HERE--- ---FIGURE 3.2b HERE---

a) Working time **b) Share of time spent on trip**

Notes: Distribution of mean hours spent logged into the Uber app, mean hours spent on trip per week, and share of time logged into the app that is spent on trip between January—March 2018 for the sample of 1,001 Uber drivers in London based on anonymized internal administrative data from Uber.

We next return to the question of whether hourly payouts vary between part- and full-time drivers. Table 3.1 reports a breakdown of hourly payouts across drivers by their

[22] One potential explanation for fewer hours worked is that some Uber drivers combine driving with other types of work activities, as discussed above. Indeed, having a business or holding another full- or part-time job is more common among drivers that drive relatively few hours with Uber. Yet, the weekly hours spent logged into the app among drivers that report no additional job or owning a business in the ORB survey is only about 1.5 hours higher at the median.

[23] When asked how many hours a respondent used his/her car for using the Uber app in an average week, the median response in the ORB survey is 40 hours. Self-reported hours, in other words, suggest that Uber drivers worked slightly longer hours than those reported by other London workers in the LFS, though drivers clearly overestimate the actual number of hours they spend in the app.

mean weekly hours logged into the Uber app. Payouts are relatively stable across the working time distribution, which suggests limited productivity differences between part- and full-time drivers. At the same time, there is significant intra-group variation, which manifests itself in a relatively wide dispersion of hourly payouts across drivers, as well as within drivers from week to week. Though hourly payouts are lower for drivers that drive at least 40 hours per week compared to those driving fewer hours, the dispersion of payouts generally tends to decrease with hours spent driving per week.

Table 3.1: Mean hourly payouts from Uber, 2018.

	Mean hourly payout (£) for drivers working:					
	>0 h/week (1)	<10 h/week (2)	10-19 h/week (3)	20-29 h/week (4)	30-39 h/week (5)	>40 h/week (6)
Median driver	16.50	16.00	17.20	16.55	16.57	16.13
(25th, 75th percentile)	(14.84, 18.17)	(12.79, 19.59)	(15.56, 19.13)	(15.14, 18.49)	(14.92, 18.08)	(14.66, 17.43)
Dispersion of hourly payouts						
Across drivers	0.20	0.43	0.17	0.16	0.16	0.16
Within drivers	0.17	0.29	0.18	0.19	0.15	0.12
Share of drivers	100%	8%	17%	25%	20%	29%

Notes: Mean hourly payouts from Uber net of its service fee for the sample of 1,001 London drivers between January—March 2018 based on anonymized internal administrative data from Uber. We present estimates for all drivers in column 1 and break down hourly payouts by the mean number of weekly hours spent in the Uber app over the sample period in subsequent columns. Across-driver dispersion of hourly payouts is calculated as the cross-driver standard deviation of mean hourly payouts divided by mean hourly payouts among drivers in each group. Within-driver dispersion is calculated as the cross-week standard deviation of mean hourly payouts divided by the mean hourly payout for each individual driver, which is then averaged across drivers in each group.

The relative stability of hourly payouts across the working-time distribution, as evident in Table 3.1, suggests that drivers can shift their hours spent driving from week to week without substantial impacts on their hourly pay. Yet, while the vast majority of drivers emphasize this choice over working hours as an important motivation to drive with Uber (see section 2.2), it remains unclear whether drivers actually use this option. To that end, we next examine the extent to which drivers adjust their working time by examining week-to-week variation in hours spent logged into the Uber app.

Figure 3.3 graphs the distribution of changes in weekly hours spent logged in to the Uber app relative to the hours in the previous week across 9,797 week-pairs for the 989 drivers (out of the 1,001 in the sample) that were logged into the Uber app in at least two consecutive weeks between January—March 2018. Evidently, drivers are adjusting the quantity of hours driving significantly from week to week by either increasing or decreasing hours spent in the Uber app. About three-quarters of all weeks driven on the platform between January—March deviate at least 10 percent from hours worked in the previous week. More strikingly, about a quarter of weeks' exhibit either positive or negative hours' deviations of 50 percent or more.

Figure 3.3: Week-to-week changes in hours logged into Uber app, 2018.

---FIGURE 3.3 HERE---

Notes: Changes in hours spent logged into the Uber app per week relative to the previous week across 9,797 week-pairs based on anonymized internal administrative data from Uber. Week-pairs are drawn from 989 (out of the 1,001) London drivers that were logged into the Uber app in at least two consecutive weeks between January—March 2018. We restrict the sample of week-pairs to those where a driver spent at least one hour logged into the app in the baseline week.

Figure 3.4: Week-pair changes in hours logged into Uber app, 2018.

---FIGURE 3.4 HERE---

Notes: Changes in hours logged into the Uber app per week and hours logged into the app in the previous week across 9,797 week-pairs based on anonymized internal administrative data from Uber. Week-pairs are drawn from 989 (out of the 1,001) London drivers that were logged into the Uber app in at least two consecutive weeks between January—March 2018. We restrict the sample of week-pairs to those where a driver spent at least one hour logged into the app in the baseline week and (for presentational purposes) with <300 percent increases in hours worked and <100 hours spent in the Uber app in the baseline week. Navy dots denote week-pairs for full-time drivers (i.e., drivers that on average spend at least 40 hours logged into the Uber app each week), while red dots correspond to week-pairs for part-time drivers (i.e., drivers that on average spend less than 40 hours logged into the Uber app per week).

Figure 3.4 sheds further light on the substantial hours' variation by plotting percentage changes in hours spent logged into the Uber app relative to the previous week for each *individual* week-pair. Navy dots denote week-pairs for full-time drivers that on average spend more than 40 hours per week logged into the app, while red dots correspond to week-pairs for part-time drivers. Again, the figure reveals the substantial variation in hours driving from week to week, also among full-time drivers. Another way to highlight this fact is to average absolute values of weekly percentage changes in hours spent logged into the Uber for each individual driver. Doing so shows that more than a third (37 percent) of all drivers on average adjust their weekly hours logged into the Uber app by 50 percent or more on a weekly basis.[24] These findings are broadly similar to those of Chen et al. (2017) and Hall and Krueger (2018) who also find that US Uber drivers shift hours significantly from week to week. Notably, consistent with the results reported in Table 3.1, this substantial variation in the quantity of hours worked among London drivers is seemingly unrelated to week-to-week changes in mean hourly payouts.[25]

A relatively weak link between working time and hourly earnings leaves the question: what drives the variation in hourly payouts across drivers? In the Appendix, we explore the role of driver characteristics in shaping mean hourly earnings. We present OLS regressions showing that the key correlate of hourly payouts is tenure on the platform either measured by years since first trip, or the total number of completed trips (see Table A.2 and A.3).[26] However, most other driver characteristics are seemingly unrelated

[24] Even among full-time drivers, a relatively large share (16 percent) adjust their hours logged into the Uber app by more than a 50 percent on a weekly basis.

[25] Across all week-pairs, the correlation between percentage changes in hourly payouts and weekly hours spent logged into the Uber app is a relatively low 0.11. Across week-pairs driven by full-time drivers, the correlation is 0.03.

[26] While the positive link between tenure and hourly payouts is suggestive of learning by doing, its interpretation is complicated by at least two factors. First, the potential selective exit of less productive drivers from the platform may induce such a positive correlation. Second, the fact that Uber's service fee varies across drivers mechanically inflates the mean hourly payouts of drivers with longer tenure. Interestingly, Cook et al. (2018) document a gender gap in earnings among Uber drivers in the US and find that it can partly be explained by differences in experience on the platform.

to payouts.[27] Although these results indicate that characteristics such as age, ethnicity, and education have little explanatory power for the variation in hourly earnings among Uber drivers, they point to the need of further inquiry into the determinants of earnings on the platform. In particular, disentangling the extent to which the variation in hourly earnings reflects demand shifts (e.g., weather) or choices about when and where to drive, compensating wage differentials (Chen et al., 2017), or driver characteristics such as gender (Cook et al., 2018) is an important avenue for future research.

3.2. How much does it pay to be an Uber driver?

Administrative data provides an extremely accurate account of the payouts that Uber drivers receive. However, it does not take vehicle operation costs into account. It therefore inevitably overstates driver earnings, since expenses incurred while driving have not been deducted. Crucially, expenses are only observed by the individual driver. We therefore proceed to approximate hourly earnings net of these costs using two distinct approaches. First, we draw on administrative data from the Uber app on mean hourly payouts for each of the 1,001 individual drivers in our sample between January—March 2018. We link this data to self-reported estimates of driver-level costs from the ORB survey, independent vehicle-level estimates of costs such as car taxes and depreciation, and TfL's estimates of the costs involved in becoming a licensed PHV driver. We describe the sources and construction of this data in detail in the Appendix. Second, we use self-reported information on income and hours driving with Uber from the ORB survey where drivers presumably deduct the expenses they have to bear.

Table 3.2: Hourly earnings among Uber drivers and London workers, 2018.

	Uber drivers hourly earnings (£) after covering expenses and hourly pay (£) for London workers							
	A. Uber drivers					B. London workers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median hourly earnings/pay	11.07	10.72	11.30	11.14	11.51	16.00	13.80	15.07
(25^{th}, 75^{th} percentile)	(8.62, 13.12)	(8.63, 12.85)	(9.64, 13.00)	(9.61, 12.45)	(8.63, 14.83)	(10.42, 25.32)	(9.17, 24.05)	(9.93, 29.80)
Expenses	Individual	Individual	Fixed	Fixed	-	-	-	-
Sample	All	Full-time	All	Full-time	Full-time	All	Distribution, transport, services	Male immigrants
Observations	854	194	1,001	217	203	1,215	391	215

Notes: Panel A reports estimates of hourly earnings net of expenses and Uber's service fee among Uber drivers. See the main text and the Appendix for a detailed description of how expenses are estimated and allocated. Panel B reports estimates of hourly pay among London workers (employed in distribution, hotels, and restaurants; transport and communication; and other services, as well as male immigrants) aged 18 and above based on data from the January—March 2018 LFS. All responses in the LFS are weighted using the

[27] A key determinant that is mechanically related to hourly payouts is differences in capacity utilization defined as the share of time logged into the app that is spent on trip. Indeed, a simple bivariate OLS regression reveals that slightly less than half of the variation in hourly payouts is accounted for by differences in capacity utilization. Notably, there is a non-negligible number of drivers that spend a small fraction of their time logged into the app on a trip (see Figure 3.2b), which are also overrepresented in the left tail of the payout distribution in Figure 3.1. Understanding what drives the variation in capacity utilization and whether it is related to drivers' choices of when and where to drive, or that some drivers are logged into the app but not 'working' is an interesting question for future work.

supplied income weights. Observations refer to the number of drivers with available data on expenses and the number of respondents in the LFS survey.

Table 3.2, panel A, presents estimates of hourly earnings net of expenses calculated as the difference between the average hourly payout net of Uber's service fee between January—March 2018 and the hourly cost estimates that include car tax, insurance, petrol, rental or repayment costs, depreciation, servicing, and licensing costs, as described in more detail in the Appendix. Column 1 shows that among the 854 London drivers for which we observe driver-level costs, the median driver earns £11.07 per hour logged into the Uber app after deducting costs incurred while driving. Column 2 restricts the sample to full-time drivers that report having no other part- or full-time job, or having their own business, and spend on average at least 40 hours logged into the Uber app each week. Estimated earnings are slightly reduced for drivers in the top half of the earnings distribution, which mainly reflects the lower average hourly payouts among this driver group noted above.

We next explore the extent to which measurement error or misallocation of individual costs may influence our estimates. To that end, columns 3 and 4 deduct a fixed hourly cost for all (full-time) drivers corresponding to the median hourly expenses within the three groups of drivers that own, finance, and rent their car respectively. We interpret these estimates as the *earnings potential* of drivers calibrated to the vehicle optimization of the median driver. After deducting expenses and Uber's service fee, the median driver can expect to earn about £11.30 per hour. Notably, earnings levels increase particularly among drivers in the bottom half of the distribution in columns 3 and 4, which indicates an important role of operational costs in shaping earnings among drivers.

As an alternative way to approximate hourly earnings levels net of expenses, we use information on self-reported income from the ORB survey, where each driver was asked about their average pre-tax monthly income and hours driving with Uber.[28] A potential caveat is that this data may also include other income streams. To identify drivers that are more likely to obtain the majority of their income from driving with Uber, we exclude drivers that reported working part- or full-time, or owning a business, in addition to being an Uber driver. We also restrict the sample to drivers that on average spend at least 40 hours per week logged into the Uber app to isolate full-time drivers, which are less likely to have other major income streams. We convert the monthly self-reported income to a weekly income and divide it by the reported hours driving with Uber in an average week to obtain an estimate of hourly earnings.

Table 3.2, column 5, presents these self-reported estimates of hourly earnings, which suggests earnings of £11.51 per hour. Hourly earnings levels drawing on this alternative source of data are broadly of a similar magnitude to the median estimates for full-time drivers of £10.72 and £11.14 in columns 2 and 4, which are derived from administrative data and estimated hourly expenses. A slightly higher level of earnings when relying on self-reported data can potentially be reconciled with these estimates by noting that the

[28] Again, the precise wording of the question in the ORB survey is: 'Thinking about your total average monthly income (before tax), what is your average monthly income?' Hours driving with Uber are derived from the question: 'In an average week, how many hours do you use your car for [using the Uber app]?'

former may include other income streams than Uber despite our sample restrictions, or that drivers are not accurately deducting expenses.

How do these hourly pay rates compare to those of other groups of London workers? An important caveat in making direct comparisons is that many conventional workers may have additional benefits (e.g., holiday pay) that are not included in their reported pay rates. Such complications notwithstanding, an interesting implication of the estimates in Table 3.2 is that the majority of Uber drivers earn above the National Living Wage standing at £7.50 prior to April 2018. Yet, as shown in panel B of Table 3.2, the estimated hourly earnings for the median Uber driver is lower than the reported hourly pay rate of the median worker in London in the January-March 2018 LFS. A similar result is obtained in a comparison with median hourly pay among workers in distribution, transport, and other services, or male immigrants that should both be relevant comparison groups in light of results discussed in section 2. At the same time, the estimated earnings for Uber drivers are broadly similar, or somewhat higher, compared to the reported hourly pay among London workers at the lower end of the pay distribution.

Figure 3.5: Hourly earnings/pay for full-time Uber drivers and low-pay workers in London, 2018.

---FIGURE 3.5 HERE---

Notes: Distribution of estimated earnings potential of full-time Uber drivers, as defined in Table 3.2, column 4. Also shown are kernel density plots of hourly pay among London workers employed in distribution, hotels, and restaurants; transport and communication; and other services, as well as male immigrants aged 18 and above in the January—March 2018 LFS. We limit all samples to workers with hourly earnings/pay below £25 that work at least 40 hours per week, and use the supplied income weights for all LFS observations.

A related question is thus how the earnings *distribution* of Uber drivers compare to other groups of low-paid workers in the London labour market. Figure 3.5 plots the distribution of the earnings potential estimates for full-time drivers from Table 3.2, column 4, and the distribution of pay among full-time London workers in distribution, transport, and other services, as well as male immigrants. For purposes of comparison, we limit all samples to individuals that report hourly pay rates below £25. Evidently, a large share of workers in distribution, transport, and other services, as well as male immigrants, in London hold jobs with hourly pay rates broadly similar to our estimates for Uber drivers. Although earnings are not directly comparable, these patterns are suggestive of labour market equilibration as the hourly earnings potential of Uber drivers is broadly similar to the pay levels in jobs that presumably reflect their outside options. This interpretation is also consistent with the results described in section 2 showing that most drivers reported leaving permanent jobs, often from the sectors depicted in Figure 3.5, to start driving with Uber.[29]

A more conceptually challenging issue in making inferences about the relative welfare of drivers based on these estimates is that Uber drivers may put a high value on non-monetary benefits associated with being an independent worker, such as choice over working hours. Indeed, it is interesting to note that Mas and Pallais (2018) find that while the average worker does not put a high value on scheduling flexibility, a small group of workers have a seemingly high willingness-to-pay. Evidence suggests that Uber drivers tend to be drawn from such groups that put a high premium on flexibility (e.g., Angrist et al., 2017; Chen et al., 2017; Hall and Krueger, 2018). As discussed above, flexibility is also a seemingly important motivation for joining Uber in London and most drivers would require substantially higher hourly pay rates to work on a fixed schedule. Thus, judging the welfare of Uber drivers based on earnings alone may underestimate their well-being if such job amenities are (partly) priced into their pay.

4. Are Uber drivers ‘uber happy’?

Against the backdrop of a rich literature documenting how job characteristics beyond monetary compensation shape individuals’ well-being, we turn to examining SWB among Uber drivers and other workers in London. Fortunately, a growing interest in alternative metrics to elicit information about individual SWB has not been limited to academic research. Official government surveys in the UK have in recent decades increasingly followed suit in measuring SWB, to aid the monitoring of national well-being, facilitate international comparisons, and help citizens to make informed decisions about their lives, such as choosing a place to live and work. In the next subsection, we discuss how SWB is measured in the APS data, which we collect for the London workforce, and for the sample of Uber drivers in the ORB survey. We then use these measures to compare the SWB of Uber drivers with other London workers, and explore the determinants of their subjective well-being.

4.1. Measuring SWB

As noted in the introduction, we focus on two different domains of SWB in our analysis—evaluative and emotional well-being—where the former captures an individual’s assessment of her life over a longer time horizon, while the latter reflects daily experiences of feelings such as anxiety or happiness. As part of the ORB survey, we incorporated several questions to elicit measures of life evaluation and emotional

[29] While the left tail of the distribution indicates that a small number of Uber drivers exhibit low earnings, this is largely explained by drivers with very low capacity utilization rates, which drives down their mean hourly payouts, as discussed above. Thus, while the patterns in Figure 3.5 are suggestive, we emphasize that the distribution of earnings should be interpreted cautiously given the challenges involved in accurately defining costs and working time for drivers in the tails of the distribution and, as noted above, we leave a detailed analysis of the individual determinants of drivers’ capacity utilization, earnings, and payouts for future work.

well-being among Uber drivers, using an identical survey methodology as the ONS. A first-order concern is that individuals may be reluctant to answer questions that probe their well-being. Yet, questions relating to an individual's happiness or well-being typically have higher response rates than, for example, questions relating to an individual's earnings (Kahneman and Krueger, 2006). Indeed, while almost a third of the drivers in the ORB survey refused to report their precise monthly income, not a single individual refused to answer any of the questions relating to their SWB.

Another concern is that the survey structure may give rise to ordering effects (e.g., Bertrand and Mullainathan, 2001). In particular, questions relating to potentially sensitive topics such as family situation or income, for example, may affect reported SWB levels. In the ORB survey, the well-being questions were therefore placed directly after an introductory set of neutral questions and the formulation and ordering of questions was identical as in the ONS surveys underlying the APS dataset. Each individual driver was asked the following four questions:

1. Overall, how satisfied are you with your life nowadays?
2. Overall, to what extent do you feel that the things you do in your life are worthwhile?
3. Overall, how happy did you feel yesterday?
4. Overall, how anxious did you feel yesterday?

and were asked to give their answer on an 11-point scale ranging from 0-10, where 0 is 'not at all' and 10 is 'completely'. An empirical concern is that imposing a cardinal interpretation of SWB measures may be problematic, as it assumes that respondents are accurately converting verbal labels such as 'not at all' and 'completely' and divides the response space into equal parts when giving their numerical answer (Clark, Frijters, and Shields, 2008). Yet, extensive evidence based on a variety of datasets shows that the assumption of cardinality of responses, or the use of linear models, typically yields very similar results to using an ordered approach (e.g., Helliwell, 2003; Ferrer-i-Carbonell and Frijters, 2004; Kahneman and Krueger, 2006).

4.2. SWB among Uber drivers and London workers

Table 4.1 reports the average responses to the four SWB questions among Uber drivers based on the ORB survey and similar estimates for employed and self-employed workers aged 18 and above residing in London drawn from the April 2017—March 2018 APS dataset. Average differences in SWB are informative, but potentially conceal a great deal of within-group variation. As a complement, we therefore also present results in Figure 4.1 using the thresholds defined by the ONS to convert the numerical responses to each SWB question into four categories ranging from 'low' to 'very high'.[30]

[30]Answers to the life satisfaction, worthwhileness, and happiness questions are here classified on a scale from low (rating 0-4), medium (5-6), high (7-8), to very high (9-10). Answers to the anxiety question is similarly classified on a scale ranging from very low (0-1), low (2-3), medium (4-5), to high (6-10). For more

Table 4.1: SWB among Uber drivers and London workers, 2017-2018.

	Uber drivers (1)	Employees (2)	Self-employed (3)
Overall, how satisfied are you with your life nowadays?	7.89	7.62	7.63
	(2.27)	(1.53)	(1.54)
Overall, to what extent do you feel that the things you do in your life are worthwhile?	7.97	7.79	7.89
	(2.08)	(1.50)	(1.49)
Overall, how happy did you feel yesterday?	7.58	7.50	7.59
	(2.77)	(1.92)	(1.85)
Overall, how anxious did you feel yesterday?	3.98	3.12	3.11
	(3.65)	(2.72)	(2.71)
Observations	1,001	5,804	1,499

Notes: Average SWB measures among three groups of London workers: Uber drivers, employees, and those reporting self-employment in their main job. All responses to each well-being question are rated on a 11-step scale where 0 is 'not at all' and 10 is 'completely'. Data is drawn from the ORB survey of 1,001 Uber drivers in London and the April 2017—March 2018 APS for (self-)employed London workers restricted to respondents aged 18 and above with non-missing responses to all four well-being questions. All responses in the APS data are weighted using the supplied well-being weights. Standard deviations are reported in parentheses.

Table 4.1 shows that Uber drivers report the highest average levels of evaluative well-being, while self-employed workers report higher levels than those in traditional work arrangements. This is consistent with an emerging body of work showing that the self-employed generally tend to exhibit higher levels of SWB in most countries, also when controlling for a range of potentially omitted (observable) characteristics (e.g., De Neve and Ward, 2017). A comparison with road transport drivers (that includes black cab and PHV drivers) also suggests that Uber drivers exhibit higher levels of evaluative well-being than the broader pool of conventional drivers, which report an average life satisfaction of 7.40. At the same time, while Uber drivers report higher levels of happiness than employed London workers, the level is marginally lower than among the broader group of self-employed.

Figure 4.1 paints a similar picture when classifying responses into the four categories applied by the ONS. Using both measures of evaluative well-being (life satisfaction and worthwhileness) and happiness, the share of individuals that report 'very high' is highest among Uber drivers. Notably, although the differences are smaller in magnitude, there is also a higher share that report 'low' SWB, which indicates that the distribution of SWB is more polarized among Uber drivers. One should, however, be cautious in attaching a causal interpretation to these differences. In particular, it is possible that individuals with a brighter outlook on life, or with personality traits correlated with higher SWB, may select into self-employment, or driving with Uber.

information, see: https://www.ons.gov.uk/peoplepopulationandcommunity/well-being/methodologies/personalwell-beingintheukqmi

Figure 4.1: SWB among London workers, 2017-2018.

---FIGURE 4.1 HERE---

Notes: Share of respondents that report 'low' ('very low') to 'very high' ('high') life satisfaction, worthwhileness, and happiness (anxiety), based on data from the ORB survey of 1,001 Uber drivers and employed and self-employed London workers based on the April 2017—March 2018 APS data restricted to respondents aged 18 and above with non-missing responses to each well-being question respectively. All responses in the APS are weighted using the supplied well-being weights.

However, Uber drivers also report much higher average levels of anxiety than other London workers, as evident in Table 4.1. Moreover, Figure 4.1 shows that the share of Uber drivers reporting either 'very low' or 'high' anxiety is higher than among other London workers, which again points to the polarization of SWB across drivers. One potential explanation for the higher average anxiety levels, presumably intuitive to anyone who has been driving in London, is that they may arise from driving *per se*. However, while the average anxiety rating among London road transport drivers of 3.21 is higher than among other employed and self-employed workers, the greater anxiety levels among Uber drivers also relative to this group suggests that the inflated anxiety can at most partly be attributed to driving in London.

Instead, an apparent trade-off between evaluative and emotional well-being among Uber drivers is consistent with evidence showing that while self-employed workers tend to report higher average levels of life evaluation, working for oneself or owning a business is also generally associated with a heightened experience of negative emotions such as anxiety, stress, or worry (De Neve and Ward, 2017). Indeed, like self-employed workers, Uber drivers may face uncertainty over earnings and pressure over the need to self-organize.[31] But while the relatively high anxiety among Uber drivers could reflect such a trade-off, anxiety levels among Uber drivers remain high also when pitched against other self-employed workers in the London population (see Table 4.1).

At least partly, the higher anxiety levels may thus be related to Uber drivers' work arrangements. For example, social scientists have suggested that digital platforms can incentivize workers to exert higher effort levels through "algorithmic control", and indeed capacity utilization rates among Uber drivers are relatively high as discussed above (Cramer and Krueger, 2016).[32] While we cannot directly disentangle the role of algorithmic control and effort-biased technological change in shaping anxiety, we provide some suggestive evidence below that effort-based explanations for the higher anxiety levels receive little support in the data. Instead, we document that Uber drivers with preferences for flexible hours exhibit higher levels of evaluative well-being *and*

[31] As noted above, one particularity of Uber drivers is that some combine driving with having a business or other jobs that may serve to increase anxiety levels. Indeed, there is some evidence that drivers having a business or holding additional part- or full-time jobs tend to report higher levels of anxiety, though such differences are imprecisely estimated (see Table A.4).

[32] Rosenblat and Stark (2016), for example, have argued that "power and information asymmetries emerge via Uber's software-based platform through algorithmic labor logistics shaping driver behavior, electronic surveillance, and policies for performance targets." More broadly, other scholars, like Green (2004), have suggested that recent technological change and new forms of work organization have led to greater managerial control over workers, which in turn leads to higher effort levels.

anxiety. Overall, this seems more consistent with the hypothesis that more autonomy at work may have differential effects on evaluative and emotional well-being.

Table 4.2: Decomposing differences in SWB: Uber drivers vs. London workers.

		Life satisfaction	Worthwhileness	Happiness	Anxiety
(1)	Uber drivers	7.923***	7.996***	7.502***	3.900***
		(0.079)	(0.071)	(0.100)	(0.126)
(2)	London workers	7.640***	7.783***	7.518***	3.145***
		(0.001)	(0.001)	(0.001)	(0.002)
(3)	Difference (1) - (2)	0.283***	0.213***	-0.016	0.756***
		(0.079)	(0.071)	(0.100)	(0.126)
(4)	'Explained'	-0.108***	0.002	0.115***	-0.261***
		(0.015)	(0.009)	(0.010)	(0.015)
(5)	'Unexplained'	0.391***	0.211***	-0.130	1.016***
		(0.081)	(0.072)	(0.100)	(0.127)
(6)	Observations	5,752	5,752	5,752	5,752

Notes: Blinder-Oaxaca decomposition of differences in SWB between Uber drivers based on the ORB survey and employed workers aged 18 and above in London based on the April 2017—March 2018 APS. We include controls for a quartic in age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), (*ln*) gross weekly income/pay, immigrant status, marital status, a set of indicators for ten self-reported ethnic groups, and sex. Standard errors derived as outlined by Jann (2008) are reported in parentheses and statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

A potentially more fundamental explanation for differences in SWB between Uber drivers and other London workers is that they arise due to compositional differences. If groups that on average are more satisfied with their lives become Uber drivers, the observed differences in evaluative well-being may simply reflect such compositional differences. To explore whether this is the case, we perform a Blinder-Oaxaca decomposition to examine whether compositional differences in terms of demographics or income can account for the gap in well-being between Uber drivers and other London workers.[33] Table 4.2 presents the results where we control for a quartic in age, educational attainment, ethnicity, immigrant status, marital status, sex, as well as (*ln*) gross weekly income/pay. As evident from Table 4.2, the 'unexplained' gap in terms of life satisfaction (and anxiety) is even larger than the raw gap. Thus, compositional differences are, if anything, biasing the relative evaluative well-being of Uber drivers downwards.[34] Naturally, this puts further emphasis on the question: why do individuals driving with Uber exhibit higher levels of life satisfaction, despite primarily being drawn from disadvantaged low-income groups in the labour market? And what explains the apparent polarization of SWB and the higher levels of anxiety?

[33] We restrict our comparisons to employed London workers because the self-employed are not reporting income in the APS dataset. We have experimented with alternative decompositions excluding income as a covariate and including self-employed workers, which yields similar results (not reported). Note that the mean SWB ratings differ marginally from those reported in Table 4.1 because respondents with missing data on covariates are excluded.

[34] We obtain similar results when estimating differences in life satisfaction between Uber drivers and London workers using propensity score matching techniques based on the same set of covariates as in the Blinder-Oaxaca decomposition. Using one, three, or five nearest neighbours and imposing common support, we find a gap in life satisfaction of 0.542 (*t*-stat = 3.58), 0.433 (*t*-stat = 3.36), and 0.448 (*t*-stat = 3.62) respectively. Consistently, gaps life satisfaction in the matched sample are thus larger than the gap observed between Uber drivers and London workers in the unmatched sample.

4.3. What explains the SWB of Uber drivers?

As a first step to understand why Uber drivers exhibit higher levels of life satisfaction, worthwhileness, and anxiety than the general London workforce, we proceed to disentangle the underlying determinants of differences in SWB among drivers. We focus in particular on three sets of factors—income, working time, and flexibility—that we evaluate in the following subsections.

4.3.1. Income and SWB

Because Uber drivers are being drawn from low-income groups in the London labour market, the fact that they on average exhibit higher life evaluation scores is at odds with absolute income levels being an important determinant of SWB. To explore the role of income, we first estimate simple OLS regressions comparing a variety of income measures and SWB among London drivers. We control for a set of demographic controls, (*ln*) mean hours logged into the Uber app per week, and a set of indicators capturing whether a driver holds another job or has a business.[35] An important concern is that attrition from the Uber platform of less satisfied drivers may mechanically inflate SWB levels in the driver pool that we observe. Therefore, we always also include tenure (number of years since first trip on the Uber platform) as a control, though we find no link between tenure and any of the four SWB measures (see Table A.4).

Table 4.3: SWB among Uber drivers: the role of income and working time.

	Outcome: SWB (0-10)						
	Life satisfaction				Worthwhileness	Happiness	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross weekly income (*ln*)	0.151			0.093	0.066	0.164	-0.150
	(0.151)			(0.134)	(0.123)	(0.171)	(0.224)
Mean hourly payout (*ln*)		-0.224					
		(0.464)					
Mean hourly earnings (*ln*)			-0.041				
			(0.175)				
Income change after partnering with Uber:							
Increased a lot (=1)				0.982***	0.670***	-0.460	0.220
				(0.223)	(0.197)	(0.368)	(0.466)
Increased (=1)				0.485***	0.187	0.455**	-0.472
				(0.178)	(0.168)	(0.227)	(0.318)
Stayed the same (=1)				.	.	.	.
				(.)	(.)	(.)	(.)
Decreased (=1)				-0.880***	-0.718***	-0.999***	-0.726*
				(0.265)	(0.245)	(0.368)	(0.426)
Decreased a lot (=1)				-1.669***	-1.273***	-1.571***	0.507
				(0.447)	(0.399)	(0.514)	(0.570)
Don't know (=1)				0.022	-0.171	-0.096	-1.428**
				(0.445)	(0.406)	(0.513)	(0.583)
Mean weekly hours spent in Uber app (*ln*)	-0.066	-0.030	-0.105	-0.122	-0.018	-0.014	0.076
	(0.137)	(0.127)	(0.138)	(0.134)	(0.124)	(0.154)	(0.225)
Demographic controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Uber controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	822	822	687	822	822	822	822
R-squared	0.047	0.046	0.048	0.133	0.094	0.074	0.040

[35] We limit our sample in the subsequent analysis to the subset of drivers with non-missing data on all controls such as age, educational attainment, and ethnicity.

Notes: OLS estimates from driver-level regressions where the outcome is one of four measures of SWB measured on a 0-10 scale. 'Demographic controls' include age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), immigrant status, sex, marital status, and a set of ten indicators for self-reported ethnic groups. 'Additional Uber controls' include a set of indicators reflecting whether a driver reports having another full- or part-time job, or having a business, in addition to driving with Uber, and tenure. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.3 show that there is no apparent relationship between life satisfaction and absolute income among Uber drivers in London.[36] Column 1 documents that the link between life satisfaction and (*ln*) gross weekly income, while positive, is small in magnitude and not statistically significant. Columns 2 and 3 reports similar non-significant relationships between life satisfaction and mean hourly payouts (net of expenses) where the estimated link is *negative*, though again small in magnitude.[37] Reassuringly, we obtain similar results in columns 5-7 when examining the link between gross weekly income and other measures of evaluative and emotional well-being. Thus, absolute income is seemingly unrelated to SWB among the pool of Uber drivers.

A growing body of work, however, argues that SWB is rather shaped by *changes* in income. Intuitively, this literature documents that individuals tend to evaluate their income in relation to their own past income and that relative increases tend to correlate positively with SWB (e.g., Clark and Oswald, 1996; Ferrer-i-Carbonell, 2005; Luttmer, 2005; Clark, Frijters, and Shields, 2008). As a first test of this hypothesis, Figure 4.2 plots life satisfaction scores among Uber drivers and whether they state that their income has increased, stayed the same, or decreased after partnering with Uber based on responses in the ORB survey. The share reporting 'very high' life satisfaction is substantially higher among respondents that perceive their income to have increased 'a lot' and decreases monotonically with smaller increases in income.[38] In other words, while drivers' absolute level of income seemingly has a limited explanatory role, Figure 4.2 is suggestive of a positive link between relative changes in income and life satisfaction.

Figure 4.2: Life satisfaction and income before and after becoming an Uber driver.

---FIGURE 4.2 HERE---

[36] We present the full regression output in the Appendix showing that most individual controls are unrelated to SWB except educational attainment and having a business/job in addition to driving with Uber, which both generally correlates negatively with SWB (see Table A.4).

[37] Note that the number of observations is reduced in column 3 mainly due to missing data on hourly expenses. As an alternative earnings measure, we have also estimated Mincer earnings regressions using the LFS to estimate the predicted pay in traditional work for each individual Uber driver based on the full set of demographic covariates. However, we find no link between SWB and the *difference* between a driver's hourly payout (net of expenses) and the predicted hourly pay in other employment based on a driver's characteristics (not reported).

[38] It is interesting to note that the mean hourly payout net of Uber's service fee is relatively stable across the distribution of perceived changes in income: drivers who state that their income decreased 'a lot' after partnering with Uber have a mean hourly payout of £16.45, while drivers who state that their income increased 'a lot' have a mean hourly payout of £16.44. A stable distribution of hourly payouts suggests that the variation in perceived income changes is driven mainly by income levels prior to driving Uber, rather than variation in hourly earnings on the Uber platform.

Notes: Share of respondents in the ORB survey of 1,001 Uber drivers that report 'low' to 'very high' life satisfaction by drivers' responses to the question: 'Since driving with Uber, do you think your average monthly income has stayed the same, increased or decreased?'. For presentational purposes, we omit the group responding 'Don't know'.

To bolster our interpretation of these patterns, column 4 of Table 4.3 presents OLS regressions that confirm a significant link between self-reported changes in income after joining the Uber platform and life satisfaction, where the omitted group is respondents stating that their income has 'stayed the same'. Notably, the pattern visualized in Figure 4.2 remains broadly unaffected when controlling for an individual's self-reported weekly income and the baseline set of controls. Moreover, the overall weaker link between relative income and emotional well-being (i.e., happiness and anxiety) in columns 6 and 7 is also consistent with the argument that income mainly affects evaluative, rather than emotional, well-being (Kahneman and Deaton, 2010). Thus, while these correlations should not be interpreted as causal links, they suggest that relative income is seemingly important in explaining the variation in evaluative well-being among Uber drivers. In other words, drivers that left lower-paid work to partner with Uber report being more satisfied with their lives, while those that saw their incomes decrease report relatively lower levels of evaluative well-being.

4.3.2. Working time and SWB

An emerging literature also shows that SWB is strongly associated with job characteristics: the level of individual autonomy, control over how the workday is organized or the pace of work, as well as work-life balance all emerge as particularly strong predictors (De Neve and Ward, 2017). In light of this, an interesting hypothesis is that the flexibility offered by the Uber platform and the fact that drivers use this extensively to shift their hours worked from week to week might help explain the relatively high levels of life satisfaction among drivers. Indeed, as shown in Table 4.3, there is no evidence of a direct link between the (*ln*) mean hours spent logged into the Uber app per week and either evaluative or emotional SWB, which suggests that there is no negative effect of long hours.[39]

A related question is whether differences in the intensity of work may shape SWB, as discussed above. Yet the link between capacity utilization rates (a proxy for effort) and anxiety is negative, and consistently positive though imprecisely estimated for life satisfaction, worthwhileness, and happiness (see Table A.5). Effort-based explanations for differences in SWB, where higher levels of work intensity lead to more anxiety and lower well-being, are thus seemingly not supported by the data, though we cannot completely rule out their relevance. For example, anxiety might derive from algorithmic monitoring rather than effort-biased technological change.

A non-existent link between hours spent logged into the Uber app and life satisfaction among drivers is interesting in light of a substantial debate over whether working long hours has a causal negative effect on SWB, or whether it simply reflects a mismatch

[39] Although estimates may differ for part- and full-time drivers, the link between hours spent logged into the app and evaluative well-being is *positive* but small in magnitude among full-time drivers (not reported), further suggesting that there exists no negative effect of long hours

between actual and preferred working time (e.g., Wooden et al 2009; Angrave and Charlwood 2015; Hamermesh et al., 2017). Uber drivers are free to drive as many hours as they want, which should reduce mismatch between actual hours worked and working time preferences.[40] Thus, a suggestive interpretation of these results is that improving choice over working hours diminishes the negative relationship between working hours and well-being observed among workers in traditional employment arrangements, suggesting it is mainly driven by mismatch and the lack of scheduling flexibility.

Table 4.4: SWB among Uber drivers: the role of flexibility.

	Outcome: SWB (0-10)								
	Life satisfaction						Worthwhileness	Happiness	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Flexibility (=1)	1.146***					0.919**	0.658*	0.965**	0.036
	(0.374)					(0.385)	(0.372)	(0.474)	(0.546)
Flexible hours (=1)		0.453**				0.251	0.317	1.682***	0.809**
		(0.210)				(0.206)	(0.202)	(0.327)	(0.361)
Choose hours (=1)			0.534**			0.357*	0.404**	0.161	0.089
			(0.207)			(0.212)	(0.189)	(0.271)	(0.359)
No traditional				0.156		-0.203	0.177	-0.296	-0.120
company (=1)				(0.234)		(0.229)	(0.216)	(0.280)	(0.390)
Independent					0.770***	0.517**	-0.032	-0.345	-1.092***
contractor (=1)					(0.226)	(0.233)	(0.194)	(0.294)	(0.377)
Demographic controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Uber controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Working hours?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	822	822	822	822	822	822	822	822	822
R-squared	0.147	0.139	0.140	0.133	0.149	0.162	0.114	0.129	0.054

Notes: OLS estimates from driver-level regressions where the outcome is one of four measures of SWB measured on a 0-10 scale. Each main right-hand-side variable is derived from the ORB survey: 'Flexibility' takes the value 1 if a driver 'agreed' or 'strongly agreed' with the statement 'I partnered with Uber to have more flexibility in my schedule and balance my work life and family'; 'Flexible hours' takes the value 1 for drivers stating they do not prefer to work fixed hours; 'Choose hours' takes the value 1 if a driver 'agreed' or 'strongly agreed' with the statement 'Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage'; 'No traditional company' takes the value 1 if a driver 'agreed' or 'strongly agreed' with the statement 'I don't want to work for a traditional company in case I lose the flexibility I have'; 'Independent contractor' takes the value 1 if a driver stated that he or she preferred to remain an independent contractor rather than be classified as an employee or worker, as described in further detail in section 2. 'Demographic controls' include age, a set of educational attainment indicators (less than high school, high school, some college, and college degree), immigrant status, sex, marital status, and a set of ten indicators for self-reported ethnic groups. 'Additional Uber controls' controls include a set of indicators reflecting whether a driver reports having another full- or part-time job, or having a business, in addition to driving with Uber, and tenure. 'Income controls' include (*ln*) gross weekly income and perceived changes in income after partnering with Uber. 'Working hours' includes (*ln*) mean hours spent in the Uber app per week. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

[40] However, since January 2018 there is an upper limit of 10 hours after which a driver cannot access the app for the next six-hour block to prevent 'drowsy driving' thus marginally reducing drivers' discretion over hours.

4.3.3. Flexibility and SWB

A majority of Uber drivers tend to emphasize the role of flexibility as an important motivation to start driving with Uber (see section 2.2). To more directly explore the potential role of drivers' preferences over flexibility in shaping SWB, we present simple OLS regressions in Table 4.4 where we correlate the four SWB measures with responses from the ORB survey indicating the extent to which a respondent's decision to start driving with Uber was motivated by flexibility.

Columns 1 and 3 show that drivers who 'agree' or 'strongly agree' with the statement 'I partnered with Uber to have more flexibility in my schedule and balance my work life and family' or 'Being able to choose my own hours is more important than having holiday pay and a guaranteed minimum wage' exhibit substantially higher levels of life satisfaction on average, conditional on an extensive set of controls including income and weekly hours spent logged into the Uber app.[41] However, differences in life satisfaction are seemingly less strongly related to preferences over working for a (non-)traditional company (column 4). Yet, drivers who state that they prefer to work flexible rather than fixed hours report higher levels of life satisfaction relative to the minority of drivers that prefer a fixed schedule (column 2). Interestingly, drivers that state that they prefer to work on a flexible schedule exhibit both significantly higher levels of evaluative well-being *and* anxiety (column 9). In general, the majority of drivers that tend to emphasize flexibility or flexible hours as a motivation to drive with Uber also generally exhibit higher levels of worthwhileness and happiness (columns 7 and 8).

Against the backdrop of these correlations, it is not surprising that the majority of drivers that state that they prefer to remain independent contractors, rather than to be classified as employees and lose their scheduling flexibility, also report higher levels of life satisfaction (column 5).[42] Moreover, these drivers also exhibit substantially lower levels of anxiety relative to those that state they would prefer to be employees or workers (column 9), which may go some way in explaining the polarization of SWB among Uber drivers highlighted above. Conversely, the minority of Uber drivers that would prefer traditional work arrangements also exhibit much lower levels of life satisfaction and higher levels of anxiety.

In our view, the correlations presented above constitute suggestive evidence that at least part of the higher evaluative well-being and anxiety among London's Uber drivers stems from a matching between (most) drivers' preferences over flexibility and the

[41] Although direct comparisons should be interpreted with caution, it is interesting to note that the relative differences in SWB between drivers that emphasize flexibility and those that do not are similar in magnitude as the gap in well-being between drivers that say that their income increased after partnering with Uber and those that say it stayed the same (see Table 4.3).

[42] An alternative interpretation of these correlations is that drivers that put a higher value on the flexibility offered by the Uber platform or prefer to remain independent contractors also have stronger 'work identity' (Bryan and Nandi, 2015), which in turn may partly explain the positive relationship with SWB. An informal test of the work-identity hypothesis is to examine whether drivers who, in the ORB survey, state that they would continue driving (with another app, or as a black cab, minicab, or PHV driver) if Uber was no longer available in their area exhibit higher levels of life satisfaction. While the relationship is positive, it is small in magnitude and not statistically significant (not reported).

autonomy that the platform offers.[43] In particular, the fact that the variation in SWB within the group of Uber drivers is polarized and tightly linked to drivers' emphasis on flexibility is highly suggestive. Moreover, while drivers who are less content with their work arrangements tend to report significantly lower levels of SWB than other Uber drivers, the mean reported life satisfaction among the minority of drivers that would prefer to be classified as employees or workers, rather than independent contractors, is similar to that reported by other drivers in London. Indeed, the minority of Uber drivers that would prefer to be conventional employees report a mean life satisfaction score of 7.34, which is close to the average reported life satisfaction of 7.40 among other road transport drivers in London. Thus, while the average Uber driver reports being more satisfied with his life than the average London worker, those drivers that place less value on the flexibility that the platform offers are seemingly no better off in terms of SWB than other drivers in the transportation sector.

5. Conclusions

Though the gig economy is still a small percentage of total employment, it is by most accounts becoming an increasingly prominent feature of work in the 21st century (e.g., Katz and Krueger, 2016; Abraham et al., 2017; Katz and Krueger, 2019). While some see this as a shift toward increasingly precarious employment, others put more emphasis on the opportunities offered to people with a preference for flexible work. For policy makers interested in the well-being of the working population, it thus seems critical to understand how workers fare as labour markets evolve. Yet, a lack of systematic measurement limits our knowledge of workers' well-being in the gig economy.

In this paper, we provide the first comprehensive statistical evaluation of work and well-being in the gig economy through the lens of Uber and its drivers in London. Drawing upon new survey data, administrative data from Uber, and newly collected data on vehicle costs, we shed light on the background, income, and SWB of the gig workforce. Our findings suggest that the typical Uber driver did not sign up to the platform as a last resort. A meagre two percent of drivers transitioned out of unemployment, and the vast majority left permanent part- or full-time jobs to start driving with Uber. Most were seemingly attracted by the flexibility that the platform offers, and use their discretion over working time to significantly adjust hours worked from week to week. It is also noteworthy that London's Uber drivers overwhelmingly come from economically disadvantaged backgrounds. About four-fifths of drivers are first-generation male immigrants, mainly drawn from the bottom half of the London income distribution. Thus, Uber seemingly constitutes an important source of work for groups that are often marginalized in the conventional labour market.

[43] In light of the fact that the majority of drivers are immigrants, a potential alternative explanation for the higher levels of life satisfaction is lower levels of discrimination on the Uber platform relative to the conventional cab and taxi sector. Yet, as shown in Table A.4 there are no statistically significant differences in life satisfaction between immigrant and native drivers, which suggests that this is a less relevant explanation. However, further work on how digital matching platforms may affect levels of ethnic and racial discrimination constitutes, in our view, an important area for future research.

While about half of drivers' report that their earnings increased after partnering with Uber, we estimate that they have firmly remained at the lower end of the London pay distribution: the median driver earns about £11 per hour spent logged into the app after both Uber's service fee and the costs incurred by driving have been deducted. Yet while being an Uber driver is relatively low-paid work, the London drivers' report higher average levels of life satisfaction than other workers. A gap in SWB persists when compositional differences are accounted for, and is seemingly unrelated to absolute income levels and working time among Uber drivers. Instead, we provide suggestive evidence that their higher SWB partly can be explained by strong preferences for flexible work among the majority of Uber drivers, and the fact that they have full discretion over working hours.

The flipside of being an Uber driver, it seems, is higher levels of anxiety. Uber drivers report substantially higher average levels of anxiety than the remainder of the London working population. This finding mirrors those of past studies showing that while self-employed workers report higher average levels of life satisfaction, working for oneself or owning a business is also generally associated with a heightened experience of negative emotions such as anxiety and stress. However, the anxiety levels across the pool of Uber drivers are highly polarized, which seemingly at least partly reflects divergent preferences for flexibility: drivers who want to remain independent contractors exhibit lower levels of anxiety, whereas roughly a fifth of the Uber driver pool, which attaches less value to flexibility, and would prefer to be classified as an employee, exhibit lower levels of life satisfaction and higher levels of anxiety. Thus, the polarization of well-being among Uber drivers' highlights a well-known challenge for policy makers. As recently put by the Taylor review on modern working practices:

> *'Hearing one person describe a job as the best they have had followed by another person describing the same job as highly stressful or exploitative highlights the challenge for policy makers in seeking to promote better work for all.'*[44]

A final important question is to what extent our findings are generalizable to other forms of flexible work arrangements, or Uber drivers in other countries. While our study provides a first step in shedding light on work and well-being in the gig economy, we caution against interpreting our findings as applicable across geographies and digital platforms for several reasons.

First, the gig economy—like the conventional labour market—consists of a broad range of segments, of which many are seemingly not comparable. For example, recent estimates suggest that median hourly earnings on Amazon Mechanical Turk are as low as ~$2 (Hara et al., 2017). In contrast, our findings suggest that the majority of Uber drivers earn above the UK minimum wage. Though direct comparisons are complicated by mandated benefits in conventional jobs, earnings on the Uber platform are seemingly

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44 See: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/627671/good-work-taylor-review-modern-working-practices-rg.pdf

similar to other low-paid jobs held by large groups of male immigrants in London. While this highlights differences in pay across two platforms, more work is surely needed to more fully understand the variation in income across countries and gig platforms, and the extent to which it is shaped by country-, platform-, and worker-specific factors.

Second, the relative attractiveness of gig work likely differs across countries, depending on labour-market institutions and prevalent economic conditions. For example, that few London drivers were unemployed prior to joining Uber is consistent with previous studies of Uber drivers in Egypt and the United States (Hall and Krueger, 2018; Rizk, 2017). In France, however, a quarter of drivers were previously unemployed (Landier et al., 2016), which possibly relates to extremely high rates of youth unemployment (Cahuc et al., 2013). Similarly, entry barriers (e.g., in terms of costs and licensing requirements) also shape individual selection patterns. While London's Uber drivers in most dimensions resemble the broader taxi driver workforce, the demographic makeup of Uber drivers in the US mirrors the general workforce rather than taxi driver population, reflecting lower barriers to entry (Hall and Krueger, 2018). Moreover, in the US, less than one in five drivers are logged into the app more than 30 hours per week (Chen et al., 2017), while about half of all Uber drivers in London spend on average 30 hours or more being active on the system, again consistent with higher barriers to entry in the UK. Thus, understanding the extent to which transitions into gig work differs across countries and how it relates to national labour-market institutions is an important area for future research.

Still, our findings have important general implications for future work on the gig economy. The preference for flexible work expressed by Uber drivers, which we find to be correlated with their SWB, suggests that evaluations of the gig economy preferably should go beyond monetary metrics. Notably, an important role of non-monetary factors also extends to more traditional work arrangements. Indeed, the latest British Social Attitudes survey shows that less than half feel that work is only about monetary compensation, and the importance people attach to income has been falling in recent years. Thus, happiness economics seemingly has an important role to play in the context of evaluating workers' welfare in the future of work.

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